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Prediction of oil consumption based on AIW-PSO wavelet neural network

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Abstract. In this paper, an adaptive inertia weight particle swarm optimization (AIW-PSO) is adopted as the learning algorithm of wavelet neural network. a AIW-PSO wavelet neural network model is established to predict oil consumption in China in a certain period. The results show that the AIW-PSO wavelet neural network model has a good prediction effect on the oil consumption.

Key words. Wavelet neural network, adaptive inertia weight particle swarm optimization (AIW-PSO), oil consumption.

1. Introduction

Oil is an important strategic material of social and economic development, the demand of consumption and the change of price volatility affects almost all sectors of the national economy [1]. So the research and prediction for the basic development trend of oil consumption in China is of great theoretical and practical significance [2].

Wavelet is a new technique in the field of time - frequency analysis, Wavelet analysis technology has time-frequency characteristics, wavelet neural network is the combination of wavelet analysis and neural network [3]. The global learning ability of wavelet neural network is stronger, the function approximation ability and the ability of pattern classification are better, the convergence speed is faster, and the generalization ability of the network is prominent [4]. In this paper, an improved wavelet neural network prediction model based on AIW-PSO algorithm is proposed and applied to predict oil consumption in China in a certain period of time.

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2. The theory of wavelet neural network

2.1. Topological structure of wavelet neural network

Topological structure of wavelet neural network is shown in Fig. 1.

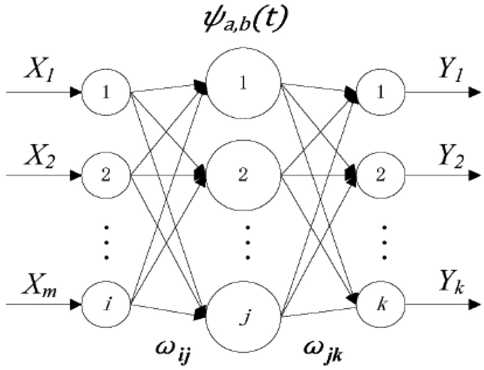

Fig. 1. Topological structure of wavelet neural network

The wavelet neural network is composed of input layer, hidden layer and output layer. It has one or more hidden layer, and each layer is composed of multiple neuron nodes [5].

$X_1, X_2, \cdots X_m$ are the input parameters, $Y_1, Y_2 \cdots Y_K$ are the output parameters, ω_{ij} and ω_{jk} are the weight coefficients for the wavelet neural network, $\psi_{a,b}(t)$ is the wavelet basis function, $X_i\,(i = 1, 2, \cdots k)$ is the input sequence, and the output formula of the hidden layer is: $h(j) = h_j \left(\frac{\sum_{i=1}^{k} \omega_{ij} x_i - b_j}{a_j} \right), j = 1, 2, \cdots, k.$

In the formula, $h(j)$ is the output of the j node of the hidden layer, ω_{ij} is the connection weight between the input layer and the hidden layer. h_j is the wavelet basis function and the b_j is translation factor of the wavelet basis function h_j, a_j is the scaling factor of the wavelet basis function h_j [6].

2.2. Selection of wavelet basis function

Wavelet basis function *Morlet* is selected as the excitation function of hidden layer [7]. It is a Gauss wave with finite support and symmetrical cosine modulation, with high frequency resolution, continuous guidance and good time-frequency localization characteristics, its function expression is

$$\varphi(t) = \cos(1.75\,t) \exp\left(-\frac{t^2}{2}\right).$$

3. Design of wavelet neural network model based on AIW-PSO algorithm

AIW-PSO algorithm is a representative of the PSO algorithm has been relatively mature [8]. In this paper, AIW-PSO algorithm is used to guide the model fitting of wavelet neural network. The optimization mechanism of AIW-PSO algorithm is added to the training of wavelet neural network as a learning strategy, and the AIW-PSO neural network is constructed to make the wavelet neural network and the AIW-PSO algorithm complement each other.

The steps of optimizing the hidden layer wavelet neural network with AIW-PSO algorithm are as follows: [9]

(1) The coefficients of the wavelet neural network are encoded as the individual particles in the AIW-PSO algorithm, and the interval is given to the population of the AIW-PSO algorithm.

(2) The AIW-PSO algorithm is used to initialize the particle population randomly.

(3) In view of the prediction of oil consumption, the network type structure, wavelet basis function and network parameters are set.

(4) The dimension information of the population is decoded into the weight coefficients of wavelet neural network model and the coefficients of wavelet coefficients, and the output of the whole network is simulated, and the mean square error of MSE is calculated to be the fitness of the algorithm.

(5) The new network model is iteratively optimized, and the algorithm is terminated when the fitness of an individual in the particle swarm meets the design requirements or the maximum number of iterations is reached.

(6) The optimal solution is decoded to the coefficients of the wavelet neural network, which makes the network performance more favorable, and then predicts the corresponding oil consumption.

4. The prediction of the oil consumption in China

There are many factors that affect the oil consumption, after repeated analysis, referring to relevant literature, this paper selects the gross domestic product (GDP), energy consumption elasticity coefficient, total energy consumption, crude oil production, net imports of crude oil and refined oil net imports of 6 indicators as input variables. The output variable is the oil consumption the same year. A wavelet neural network prediction model based on AIW-PSO algorithm is constructed.

4.1. The collection and preprocessing of data samples

This paper collected data from 1990 to 2014 with the historical data of oil consumption, including gross domestic product (GDP), energy consumption elasticity coefficient, total energy consumption, crude oil production, net imports of crude oil, refined oil net import s and oil consumption. The data derived from the China Energy Statistical Yearbook, The information of the sample data set is from 1990 to 2014, a total of 25 sets of sample data, including training samples for the first 19 groups, and the latter 6 sets of data for the test sample. The following Table 1 is partial sample data.

Table 1. Table of statistics in 1999–2004 years

year	GDP (Million yuan)	Elasticity coefficient of energy consumption	Total energy consumption (million tons of standard coal)	Crude oil production (Million Tons)	Net import of crude oil (Million tons)	Net import of refined oil (Million tons)	The oil consumption (Million tons)
1999	8967700	0.16	1338.31	160	29.447	16.762	209.60
2000	9921500	0.42	1385.53	163	59.96	13.795	223.60
2001	10965500	0.41	1431.99	163.96	52.71	15.912	227.90
2002	12033300	0.66	1517.97	167	61.75	17.108	247.40
2003	13582300	1.53	1749.90	169.60	82.887	22.393	271.70
2004	15987800	1.59	2032.27	175.87	117.23	32.863	318.90

Source: China Energy Statistics Yearbook

In the collected data, the dimensions of each factor are inconsistent, and the prediction may lead to greater differences in prediction results due to dimensional differences. Since the output interval of the activation function of the neural network is [0, 1], if the data normalization is not performed, the output of the sample exceeds the output range of the neural network. The activation function of the neural network changes very slowly in the range of [0, 0.1] and [0.9, 1], and it is easy to fall into the saturated zone of the neural network, Therefore, the inputs should be normalized to the [0.1, 0.9] range. To do this, use the following data normalization method:

$$x' = \frac{0.8 \cdot (x - x_{\min})}{x_{\max} - x_{\min}} + 0.1\,.$$

The corresponding data normalization reduction formula is as follows:

$$x = 1.25(x' - 0.1)(x_{\max} - x_{\min}) + x_{\min}\,.$$

4.2. The setting of related parameters in AIW-PSO algorithm

The determination of the number of neurons in the input layer and output layer of the neural network needs to be determined according to the input parameters of the actual problem and the output parameters. The nature of the system input variables determines the network structure to be adopted by the neural network system. In this paper, the input variables are the gross domestic product (GDP), energy consumption elasticity coefficient, total energy consumption, crude oil production, net imports of crude oil and refined oil net imports of six factors, the output variable is the oil consumption. Therefore, the number of nodes in the input layer is 6, and the number of nodes in the output layer is 1. According to the empirical formula and repeated tests, the number of hidden layers is 10. At this time, the particle size of AIW-PSO algorithm is $D = 6 * 10 + 10 * 1 + 10 + 10 = 90$, and the number of particles is $S = 40$, The particle individual parameter initial range is set as $[-1, 1]$, the learning factors c_1 and c_2 are set to 2., the velocity limit of the particle is set to 0.5, the lower limit of velocity is -0.5, the maximum value of the particle position is 1, and the minimum position is -1.

From the basic principle of PSO algorithm in position and velocity equation, the inertia weight ω_{ij} is non negative, it makes the particles keep moving inertia, which has extended space contraction trend, contribute to the new search area. The equation of adaptive inertia weight ω is:

$$\omega = \omega_{\max} - k(\omega_{\max} - \omega_{\min})/k_{\max}$$

in the upper form, $\omega_{\max}$ is the maximum inertia weight, $\omega_{\min}$ is the minimum inertia weight, and k is the current iteration number, $k_{\max}$ is the total number of iterations.

According to the optimization ability of individual particles, the global search ability and local development capability are adjusted by adaptive inertia weight. Each particle of each dimension has different inertia weights at each iteration, which will be beneficial to improve the convergence accuracy. The inertial factors $\omega_{\max}$ and $\omega_{\min}$ are set to 0.9 and 0.4 respectively.

4.3. The setting of neural network parameters and simulation experiment results

In this paper, the mean square error *MSE* and the mean absolute percentage error *MAPE* are used as the evaluation criteria of the wavelet neural network in the prediction of oil consumption [10]

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2; \quad MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right|.$$

In this paper, in order to verify the prediction effect of the improved wavelet neural network model, the traditional wavelet neural network in Matlab7.0 toolbox is compared with the improved wavelet neural network. Particle population size generally takes 80, the number of iterations is set to 500, and the rest parameters adopt the default value of Matlab7.0 neural network toolbox.

In order to reflect the superiority of the improved algorithm prediction, the AIW-PSO wavelet neural network prediction model is compared with the traditional wavelet neural network prediction model, two prediction model procedures tested 5 times in Matlab7.0 environment respectively, the test results are given in Table 2 as follows:

Table 2. Comparison of algorithm results

Comparison of algorithm results	Wavelet neural network	AIW-PSO Wavelet neural network
Train MSE	0.0264	0.0236
Test MAPE	1.69%	1.17%
Iteration number	100	500
training time (S)	2.67	325.15

From the experimental results, we can see that the AIW-PSO wavelet neural network is better than the traditional wavelet neural network in the stability and prediction accuracy of the prediction results.

The following Fig. 2 is a data graph of using AIW-PSO wavelet neural network to predict China's oil consumption in the past 2009–2014 years.

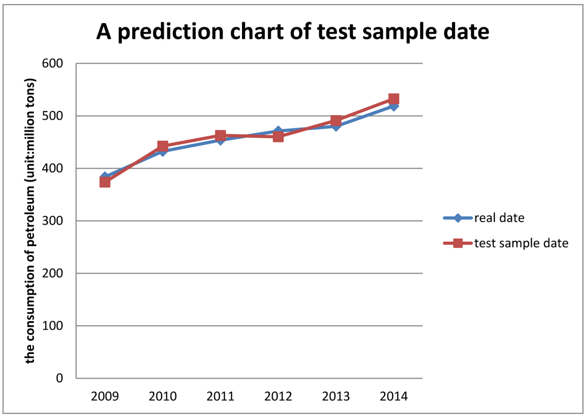

Fig. 2. A prediction chart of test sample date

5. Conclusion

Based on the data of China's oil consumption in the past years 1990–2008, a AIW-PSO wavelet neural network model is established to predict the oil consumption in China in the past years 2009–2014. The results show that the adaptive inertia weight particle swarm optimization algorithm can be used to train the wavelet neural network, and it has very good network weights and system optimization effects. AIW-PSO wavelet neural network prediction model will become a new prediction tool of hybrid algorithm.

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